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Towards globally customizable ecosystem service models

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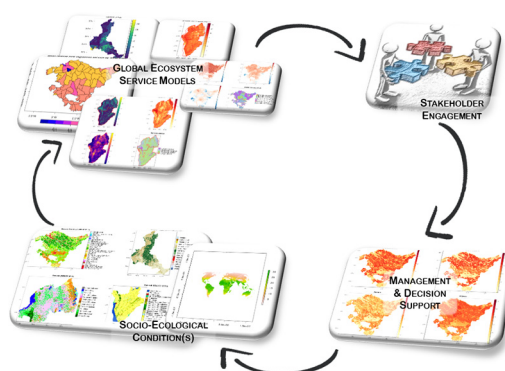
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HIGHLIGHTS

- Ecosystem service (ES) modeling is typically time consuming.
- Limited data and model reuse hinder new applications and progress in the field.
- We demonstrate 5 cloud-based ARIES models that can run on global or customized data.
- Models produce consistent outputs, including ES supply, demand and surplus/deficit.
- Community-level data and model sharing can advance progress in ES modeling.

GRAPHICAL ABSTRACT



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ABSTRACT

Scientists, stakeholders and decision makers face trade-offs between adopting simple or complex approaches when modeling ecosystem services (ES). Complex approaches may be time- and data-intensive, making them more challenging to implement and difficult to scale, but can produce more accurate and locally specific results. In contrast, simple approaches allow for faster assessments but may sacrifice accuracy and credibility. The Artificial Intelligence for Ecosystem Services (ARIES) modeling platform has endeavored to provide a spectrum of simple to complex ES models that are readily accessible to a broad range of users. In this paper, we describe a series of five “Tier 1” ES models that users can run anywhere in the world with no user input, while offering the option to easily customize models with context-specific data and parameters. This approach enables rapid ES quantification, as models are automatically adapted to the application context. We provide examples of customized ES assessments at three locations on different continents and demonstrate the use of ARIES’ spatial multi-criteria analysis module, which enables spatial prioritization of ES for different beneficiary groups. The models described here use publicly available global- and continental-scale data as defaults. Advanced users can modify data input requirements, model parameters or entire model structures to capitalize on high-resolution data and context-specific model formulations. Data and methods contributed by the research community become part of a growing knowledge base, enabling faster and better ES assessment for users worldwide. By engaging with the ES modeling community to further develop and customize these models based on user needs,

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spatiotemporal contexts, and scale(s) of analysis, we aim to cover the full arc from simple to complex assessments, minimizing the additional cost to the user when increased complexity and accuracy are needed.

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1. Introduction

Over a decade after the publication of the Millennium Ecosystem Assessment (MEA, 2005), ecosystem service (ES) modeling is slowly becoming a more mature field. Abundant examples of ES modeling applications from local to global scales now exist (Maes et al., 2015; Ochoa and Urbina-Cardona, 2017). Large-scale, global assessments are also driven by policy needs that support initiatives such as the Intergovernmental Platform on Biodiversity and Ecosystem Services (IPBES; Pascual et al., 2017), the U.N. Sustainable Development Goals (SDGs; U.N., 2017), and natural capital accounting, including wealth accounts and the System of Environmental-Economic Accounting (Bagstad et al., 2018b; U.N., 2014).

Ideally, the next generation of ES models will be accessible and rapid, yet customizable, efficiently reusing place-specific data and knowledge. Reducing the effort needed to produce an ES assessment is important for delivering timely results to decision makers and stakeholders, so that ES information does not arrive after the decision window has closed (Ruckelshaus et al., 2015). Model and data customization are important for capturing local knowledge, improving credibility, and reducing the inherent inaccuracies of global and other large-scale data (Cerretelli et al., 2018; Zulian et al., 2018). Ideally, customization would extend beyond input data to include model structure, accounting for key differences in how ES are generated (Smith et al., 2017) and used by people (Wolff et al., 2017). Customizable ES models capable of synthesizing and reusing dispersed knowledge could help break from the long-standing dichotomy of using one-size-fits-all versus place-based approaches for ES assessments (Carmen et al., 2018; Rieb et al., 2017; Ruckelshaus et al., 2015).

In recognition of these limitations, efforts are underway to adapt ES modeling platforms for global application, e.g., Artificial Intelligence for Ecosystem Services (ARIES; Villa et al., 2014), Co\$ting Nature (Mulligan, 2015), and Integrated Valuation of Ecosystem Services Tradeoffs (InVEST; Sharp et al., 2015). Co\$ting Nature is a web-based tool with preloaded models and datasets that supports ES assessment anywhere on Earth. Version 3.0 (currently in beta) enables the assessment of 12 ES, but does not support model customization by users. Moreover, options to run analyses at moderate to high resolution and output results in biophysical units rather than index values require a paid subscription. InVEST's global application adapts their existing suite of models (Sharp et al., 2015) in a development build based on InVEST 3.4.4, incorporating global datasets and model coefficients (Kim et al., 2018). While the InVEST global models are under development, the model code and coefficients are available from a publicly available code repository and the input data are available as described by Kim et al. (2018). Few of these large-scale modeling platforms enable customization with local data, parameterizations, or adjustments to model structure to reflect local knowledge of processes that underlie ES supply and demand. For example, Kim et al. (2018) apply a global mean parameter dataset to running InVEST. Zulian et al. (2018) provide an example of the customization of the Ecosystem Services Mapping Tool (ESTIMAP), a European ES modeling platform (Maes et al., 2015), and provide guidelines to make model customization more scientifically robust and decision relevant. However, the source code of the models is not yet publicly available and cannot be directly reused or adapted by users.

In this paper, we describe the ARIES modeling platform's approach to developing global, yet customizable ES models. Our approach endeavors to balance tensions between the demand for complexity, through model customization and data integration to reflect biophysical and socioeconomic conditions and behaviors, and simplicity, as data

limitations and user needs may require abstraction and simplification of some ES models. Simple ES models are suitable to support some resource management decisions (Willcock et al., 2016), while others require information generated by more complex models. As such, the linking of simple and complex ES models can help support adaptive management by providing timely information that can easily be updated and reevaluated as new data and knowledge become available. In this paper, we describe models that can provide a “bottom line” strategy for rapid assessment and prioritization, while ensuring consistency in outputs among different ES and adaptability to trade-off analysis, as the first tier of a seamless path to adaptive complexity and automated integration of ES models (Villa et al., 2014).

Our approach to automated model customization expands the role of global ES models, enabling navigation between different model tiers based on ES assessment needs, time and data availability. A “Tier 1” approach, analogous to tiered approaches to forest carbon monitoring under Reducing Emissions from Deforestation and Forest Degradation (REDD+; Angelsen et al., 2012), ES models proposed in InVEST (Kareiva, 2011) and other environmental modeling approaches (Günther et al., 2013), is interpreted here as a base for customization and a default strategy to use when better models (e.g., dynamic flow models; Bagstad et al., 2013) are not available. The ARIES model base also includes several Tier 2 models, such as a dynamic agent-based pollination model that quantifies flows of pollinators between habitat patches and pollination-dependent crops, and water supply models employing dynamic, distributed surface runoff simulation. Such models are currently too computationally intensive for large-scale application, and, like any modeling approach, require calibration if accurate outputs are desired. Once ARIES is supplied with decision rules about the appropriate scale and spatiotemporal context under which to run each model tier, it can seamlessly navigate between tiers as spatiotemporal context and resolution change, and as more data and models become available.

These Tier 1 models provide a baseline for subsequent specialization and customization. When semantically annotated data covering new spatial and temporal extents or resolutions are made available either locally on a user's computer or on the network, the annotated concept (Janowicz et al., 2015) described in the data enables ARIES to automatically substitute local data for global where appropriate (Villa et al., 2014, 2017). For instance, a local or national-scale dataset for “percent tree canopy cover” will replace a global dataset for the same observable when a model requires that input and is run in a compatible time and place. New models or adjustments to existing models can be specified for a particular time, place, or spatiotemporal scale, and may cover all concepts related to an ES or only a *component concept* of it (e.g., its supply or demand). Because ARIES is a *context aware* modeling system, the best available knowledge will be reused for the context analysed. The system assembles a computational strategy, based on a set of rules under which data, models, and model parameterizations are selectively applied (Villa et al., 2014), which is run to produce both the desired outputs and associated provenance information (Villa et al., 2014). The latter is compiled into a report detailing the provenance of all input data and the algorithms used to produce the modeled outputs (Willcock et al., 2018). We thus lay the foundation for an intelligent ES modeling platform that can improve model credibility by more systematically incorporating and reusing local knowledge (Zulian et al., 2018). As more data and models are shared on the semantic web used by ARIES, the accuracy, speed and credibility of ES assessments can be substantially improved.

This work supports progress towards several long-anticipated goals in ES modeling specifically and semantic modeling more generally

(Villa, 2009). Past ARIES applications were place-based case studies (e.g., Bagstad et al., 2014; Balbi et al., 2015), meaning that ARIES models could be run only for a relatively small number of locations. The availability of global data and models, hosted on networked geoservices, now enables their computation anywhere. The collection of models described here is accessible through the Knowledge Laboratory (k.LAB) Integrated Development Environment (ARIES team, 2017), the open source software package used by ARIES (Fig. 1 describes the user workflow). In order to run models, the user must select a spatiotemporal context, model resolution, optional scenario condition(s), and the underlying ES concepts to be observed (e.g., supply or demand; ARIES team, 2018a). The k.LAB software package also provides the tools to write new models or customize existing ones. A web-based ARIES explorer, currently in prototype stage and slated for public release in early 2019, will make it possible to run ARIES models online through a web browser, making models more accessible particularly for nontechnical users.

In this paper, we describe methods and results for five ARIES Tier 1 models. We demonstrate model applications in three continents, and extend one of those applications to include a spatial multi-criteria analysis, which enables simple trade-off and prioritization analysis in ARIES. These models will continue to be developed and new models will be added to the model library by the ARIES core development team and collaborators. The aim is for any ARIES modeler to be able to use them, develop customizations for specific local conditions, or improve and share the models for the benefit of the broader ES modeling community.

2. Methods

A publicly accessible code repository (ARIES team, 2018b) containing all models and spatial context definitions used for this paper is available for download and use. Our model developer workflow, which used k.LAB version 0.9.11, is shown in Fig. 1. Detailed information on all data sources and lookup tables used for each model in this study can be found in the Supplemental Information. Input data without use restrictions (e.g., public data) can be accessed through networked geoservices available to any ARIES user. All model outputs for the three application areas are available from the authors upon request.

We developed models for the supply of five ES: carbon storage, crop pollination, flood regulation, outdoor recreation, and sediment regulation. We modeled demand for crop pollination, flood regulation, and outdoor recreation, ranking locations of greater and lesser demand, but not considering demand in monetary terms. We did not estimate demand for carbon, a global service whose demand can be proxied using greenhouse gas emissions data (Bagstad et al., 2014), nor for sediment regulation, where different, context-dependent beneficiary groups can be identified. Our models for ES supply and demand for crop pollination, flood regulation, and outdoor recreation are estimated as ranked indicators, rather than biophysical values. For crop pollination and flood regulation, we also developed a metric of surplus or deficit, which simply subtracts normalized ES demand from supply to calculate a surplus/deficit value (ES_{sd}), where negative values represent a deficit and positive values represent a surplus. This metric can be used to understand potential threats to ES provision (Maron et al., 2017; Wei et al., 2017). Large versus moderate surplus/deficit subcategories were also considered based on values above or below ± 0.5 , but we caution that given the use of normalized, uncalibrated model outputs not on the same scale, care be taken in interpreting surplus/deficit results. To account for the hydrological connection between grid cells located within the same watershed, we also enabled the calculation of ES_{sd} for water-related ES (e.g., sediment or flood regulation) by aggregating grid-cell values on a sub-watershed basis, using globally available watershed polygons (Lehner et al., 2008).

As example model customization applications, we chose regions on three continents that use varying levels of customization based on the best available input data. Thus, we selected the Basque Country (Spain), a multi-watershed region surrounding the Santa Fe Fireshed (U.S.), and Rwanda and Burundi (Africa) (Fig. 2). The Basque Country is a diverse region in northeast Spain covering 7234 km² that can be divided into three distinct geographic regions from north to south: the mountainous Atlantic region, a central plains region (the Llanada Alavesa) and the Ebro Valley. The northern valleys have an oceanic climate, whereas the rest of the region has a more continental one. About half of the region's 2.2 million residents live in the Bilbao metropolitan area; San Sebastián and Vitoria-Gasteiz are other major population centers. The Santa Fe Fireshed, a region defined by shared social and

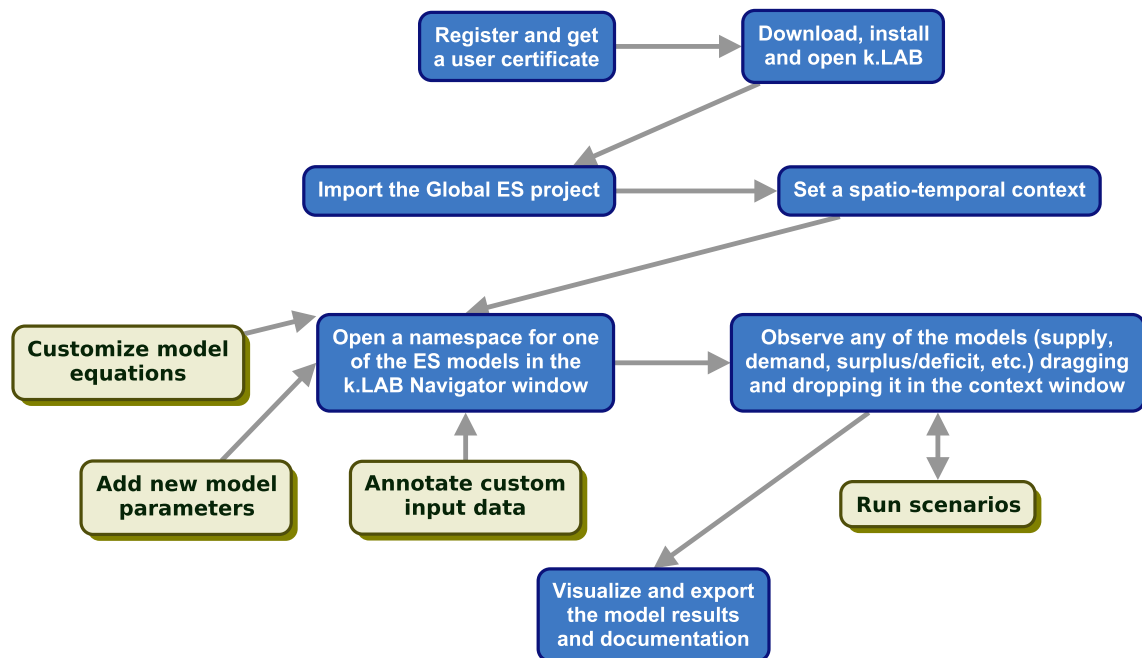


Fig. 1. Model developer workflow for the use of the global ecosystem service (ES) ARIES models in the k.LAB software package. Steps in blue are those taken to run existing Tier 1 models using default data sources; those in beige represent opportunities to customize model source code, data resources, and scenarios.

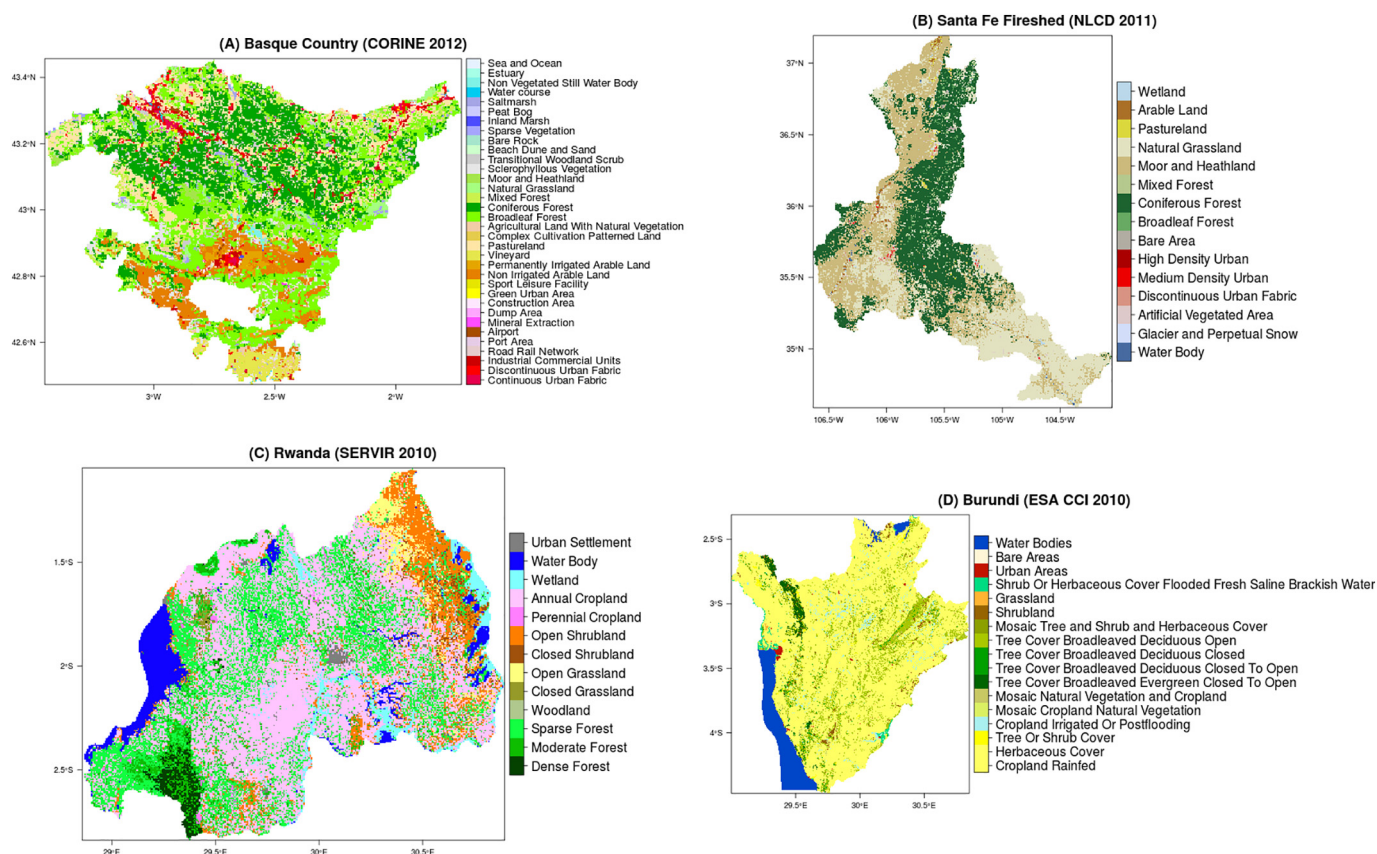


Fig. 2. Land cover datasets used for each context: (A) Coordination of Information on the Environment (CORINE) 2012 in the Basque Country; (B) National Land Cover Database (NLCD) 2011 in Santa Fe Fireshed, New Mexico; (C) SERVIR 2010 in Rwanda; (D) European Space Agency-Climate Change Initiative (ESA CCI) 2010 in Burundi.

ecological concern regarding the impacts of wildfires, is located in northern New Mexico. Land ownership includes a mix of types including tribal, private, public, and non-governmental organizations. The fireshed boundary encompasses nearly 430 km², and the study area addressed here extends this boundary to include the three watersheds to which it is hydrologically connected, totaling ~22,300 km². A majority of the population within the study area resides in the cities of Santa Fe and Albuquerque. Mid-elevation areas have historically featured open stands of ponderosa pine (*Pinus ponderosa*), which tend to be shaped by regularly occurring, low-severity fires, while higher elevation areas are more susceptible to high-severity fires in the driest years (Margolis and Swetnam, 2013). Rwanda and Burundi are two small equatorial African nations totaling 54,172 km². Both are densely populated nations that have experienced periodic civil unrest since independence, though Rwanda has seen substantial economic development in a period of stability dating to the early 2000s. Rwanda and Burundi are situated within the Albertine Rift zone and have varied topography and precipitation; land cover is dominated by cropland, with forests and other natural land cover types found most abundantly within protected areas. We modeled ES for Rwanda and Burundi building on past national-scale ES modeling for Rwanda (Bagstad et al., 2018a). Land cover data for ES modeling in Rwanda are available at 30 m resolution through the Regional Centre for Mapping Resources for Development (RCMRD), a GIS and mapping center working across Eastern and Southern Africa. Such data are not available for Burundi, so the model configurations for the two nations illustrate different levels of data customization. The Santa Fe Fireshed and Basque Country applications offer examples of greater levels of model customization in more data-rich regions. All of our models use lookup tables to account for the role of land cover in providing ES. For all ES but recreation, we provide global values for lookup tables based on past studies, and customize the tables based on context-specific research when possible (Supplemental Information,

Table S3). Although global lookup table values may suffice for initial ES estimates, locally derived lookup tables are essential for improving model credibility and application for decision-making.

We applied the ES models at different spatial resolutions depending on the size of the study area size and ES being modeled. For all ES except pollination, the Rwanda and Burundi application was modeled at a 200 m resolution, the Santa Fe Fireshed at 250 m, and the Basque Country at 300 m. The pollination model was run at 1 km resolution for all applications. We selected data inputs as close as possible to the year 2010, and fully describe all input data in the Supplemental Information. More detailed studies describing the application and results of these models in different contexts can be found in other articles of this issue (Barbosa et al., this issue; Domisch et al., this issue; Funk et al., this issue).

2.1. Pollination

Pollination by animals is an essential ES that directly links natural habitats to agricultural landscapes, as 70% of globally important crop species depend to some extent on pollinators (Klein et al., 2007). The pollination model produces spatially explicit, ranked estimates on the supply and demand for insect pollination services based on land cover, cropland, and weather patterns. All pollination analyses are run at 1 km, which is similar to the flight distance of most insect pollinators (Danner et al., 2016; Gathmann and Tschardt, 2002).

In its first step, the model calculates pollination supply, or the ability of the environment to support wild insect pollinators, as a function of nesting suitability (NS), floral availability (FA) and proximity to fresh-water bodies (i.e., rivers, lakes and streams). We assigned NS and FA values to land cover categories using lookup tables based on expert opinion from previous studies (Lonsdorf et al., 2009; Zulian et al., 2014). The model assumes a positive effect on the probability of

pollinator presence from freshwater bodies (due to assumed greater floral resources in riparian areas, [Zulian et al., 2013](#)). The model maps pollinator habitat suitability as a proxy for pollinator abundance, as the product of NS and FA, given that both variables need to be simultaneously present to support pollinator populations. Then, to account for the increase in habitat suitability to support pollinator populations in areas close to freshwater resources, the inverse distance value to freshwater bodies is added to the result of the previous product. Insect foraging can also be greatly affected by atmospheric temperature and solar radiation, which can affect the number of active individuals ([Corbet et al., 1993](#)). We thus calculated the proportion of active individuals foraging (A) as:

$$A = -39.3 + 4.01 \times T_{\text{blackglobe}} \quad (1)$$

where $T_{\text{blackglobe}}$ represents the temperature of an insect's body simulated as a black spherical model as a function of annual mean ambient temperature (T in °C) and annual mean solar irradiance (R in W m⁻²):

$$T_{\text{blackglobe}} = -0.62 + 1.027 \times T + 0.006 \times R \quad (2)$$

We then normalized habitat suitability and multiplied normalized values by the proportion of active individuals foraging to account for spatial differences in pollinator activity levels.

Next, the model estimates pollination demand based on the product of the weighted sum of crop pollination dependencies ([Klein et al., 2007](#)) and their production for 55 crop types requiring insect pollination for optimal yields ([Monfreda et al., 2008](#)). The model normalizes pollination-dependent crop production based on the values found within the user-selected spatial context in order to compute pollination surplus/deficit. To simplify the computation, we assume the flow of the pollination service to be restricted to the grid cell within which the pollinator resides (i.e., no supply is received from adjoining cells). Finally, the model subtracts demand from supply to produce grid cell-scale pollination surplus/deficit values.

2.2. Carbon storage

The global vegetation carbon storage model follows the Tier 1 Intergovernmental Panel on Climate Change (IPCC) methodology and quantifies above- and below-ground carbon storage in vegetation in physical units (T/ha), using a lookup table. The model's lookup table uses five datasets as inputs, following [Ruesch and Gibbs \(2008\)](#): (1) land cover, (2) ecofloristic region ([FAO, 2000](#)), (3) continent, (4) frontier forests—a proxy for the degree of forest degradation ([Potapov et al., 2008](#)), and (5) presence of a recent fire (i.e., within the last 10 years) ([Tansey et al., 2008](#)). This model provides globally consistent estimates of the amount of carbon stored in above- and below-ground vegetation ([IPCC, 2006](#); [Ruesch and Gibbs, 2008](#)). Additionally, soil carbon storage estimates can be modeled, e.g., using global SoilGrids data ([Hengl et al., 2017](#)).

2.3. Outdoor recreation

The recreation model is inspired by the ESTIMAP model of nature-based outdoor recreation developed by [Paracchini et al. \(2014\)](#) for Europe, and calculates supply and demand using ranked values. The model computes recreation supply as a multiplicative function of naturalness and the distance-driven accessibility of nature-based factors of attractiveness, computed as Euclidean distance to protected areas (extracted from the World Database on Protected Areas; [UNEP-WCMC and IUCN, 2016](#)), mountain peaks (extracted based on the top fraction of terrain height values in the study area), and water bodies (including streams, lakes and oceans). The model computes the degree of naturalness as a reclassification of land cover types into numerical values

ranging from 1 to 7, with higher values representing increasing land use intensity/human influence ([Paracchini et al., 2014](#)).

Finally, the model discretizes normalized recreation supply values into three recreation potential classes (<0.75, 0.75 to 0.88, and >0.88), which produced values similar to those from the ESTIMAP implementation of the Recreation Opportunity Spectrum (ROS; [Clark and Stankey, 1979](#); [Joyce and Sutton, 2009](#); [Paracchini et al., 2014](#)). The ROS reclassifies the landscape by recreation potential (i.e., recreation supply as described above) and proximity to people. The model estimates proximity to people based on travel time to the nearest city with ≥50,000 inhabitants ([Uchida and Nelson, 2010](#)). We used a dataset for travel time ([Nelson, 2008](#)), which we normalized and discretized into three classes (easily accessible: ≤0.25; accessible: 0.25 to 0.5; and not accessible >0.5).

In addition to ESTIMAP's ROS classification, our model quantifies recreation demand as an additive function of population density and recreation-driven mobility. The latter describes how far an individual is likely to travel for recreation on a day trip. The mobility function, adapted from [Paracchini et al. \(2014\)](#) and originally based on [Geurs and van Eck \(2001\)](#) models the probability of traveling to a site as a function of distance, assuming high probability of trips within 30 Km and very low probability at 80 Km:

$$f(d) = (1 + K) / (K + e^{(a \cdot d)}) \quad (3)$$

where d is the distance from a site and K and a are parameters describing the shape (S-shape) and scale of the log-logistic function ([Geurs and van Eck, 2001](#)), respectively. We further customized this function by adding a dependency on estimated travel time ([Uchida and Nelson, 2010](#)):

- d is the distance to main cities (automatically queried in OpenStreetMap at runtime); when travel time is >30 min, then $d = d + 30$ km. This creates a 30 km buffer for short trips around main cities, where the likelihood of high recreation demand is much greater, and
- the mobility function parameter values are set to $K = 450$ and $a = 1.12E - 04$, which combines the long- (80 km) and short-distance (8 km) functions in [Paracchini et al. \(2014\)](#).

Recreation demand takes into account the likelihood of taking a day trip to a certain point and the population density in the areas serving as a source of visitors for that location, thus describing the relative number of trips taken from each grid cell within the context. In this way, the model uses estimated travel time to calculate the flow of recreation demand from population centers to recreational sites.

In addition to the previously described ES_{sd} analysis, we propose a multiplicative Cobb-Douglas-type function to relate recreation supply and demand, which takes the form ([Fuleky, 2006](#)):

$$f(S, D) = p \cdot S^x \cdot D^y \quad (4)$$

where $p = 1$, $x = y = 1/2$, and S and D are recreation supply and demand, respectively. This estimates the spatial overlay of supply and demand expressed with a weakly concave function representing landscape recreational utility. It is a symmetric function with constant return to scale (the service increases by that same proportional change as supply and demand change) and diminishing marginal utility. This output facilitates the identification of sites with high recreation supply and demand, where outdoor recreation day trips are most likely to happen. Such areas receive a value closer to one; areas with low supply or demand receive values closer to zero.

In order to adapt the European-based recreation model for global use, we made several simplifications that preclude the direct comparability of results to European ESTIMAP recreation model outputs

(Paracchini et al., 2014). These include the use of European-derived, land cover-based estimates of naturalness and proximity thresholds, which may differ by ecoregion and socioeconomic setting, respectively. Both would be best informed by local parameterizations provided by region-specific experts (Baró et al., 2016; Peña et al., 2015). We also excluded water quality from the recreation potential assessment, due to a lack of global data. Finally, the concept of outdoor recreation and the model's parameterization, which implies travel by vehicle to outdoor recreation sites, makes the existing model most suitable to developed-world contexts. However, the model's basic components (attractiveness, demand, and accessibility) could be adjusted to account for non-vehicular access to green space in cities or tourist access to protected areas, which may be useful in both developed and developing-world contexts.

2.4. Flood regulation

This model quantifies ranked values for flood regulation supply and demand, accounting for flood hazard probability, water retention by soils and vegetation, and population density. Flood hazard probability (FHP) is estimated based on: (1) topographic wetness index (TWI), a steady-state wetness index based on slope and contributing area (Kirkby and Beven, 1979; Manfreda et al., 2011), (2) mean annual precipitation, and (3) the mean temperature of the wettest quarter (Hijmans et al., 2005). Temperature is included in the equation to account for the role of the Clausius-Clapeyron relationship (Trenberth et al., 2003), which predicts greater rainfall intensity at higher temperatures. Based on Utsumi et al. (2011), the model uses mean atmospheric temperature in the wettest quarter to predict an increase in the temperature-rainfall intensity relationship in polar regions (high latitudes), a decreasing relationship in equatorial regions (tropics), and a peaked relationship in temperate regions (intermediate latitudes). The model computes flood regulation supply (FRS) using the Curve Number (CN) method, which estimates the capacity of vegetation and soils to retain excess runoff from rainfall. The CN is a function of land cover, hydrologic soil group data, and in some contexts slope (Zeng et al., 2017; Soil Conservation Service, 1985). The model then reduces flood hazard probability by the CN:

$$\text{FRS} = \text{FHP} - (\text{CN} * \text{FHP}/100) \quad (5)$$

The model estimates flood regulation demand by multiplying FHP by population density, providing a ranking of the relative exposure of people and property to flood risk. Finally, the model estimates ES_{sd} as previously described. This value can be aggregated by watershed (predefined or user-supplied) within the spatial context. This model thus constitutes a simplification of previously published global or continental-scale ones (Stürck et al., 2014; Ward et al., 2015), but is fast and easily replicable even in data-scarce contexts.

2.5. Sediment regulation

Our sediment regulation model is an implementation of the commonly used Revised Universal Soil Loss Equation (RUSLE; Renard, 1997), and provides biophysical estimates of soil loss and retention by vegetation (in tons of sediment per hectare per year). The RUSLE model estimates annual soil loss based on five factors:

$$A = R * K * LS * C * P \quad (6)$$

where A represents soil loss, R rainfall runoff erosivity, K soil erodibility, LS slope steepness and length, C cover management, and P conservation practice.

This implementation of RUSLE uses methods from Van Remortel et al. (2004) to calculate LS, based on slope and contributing area, Williams and Singh (1995) to calculate K, based on soil organic matter

and clay, sand, and silt fractions, and global studies for C and P factors based on land cover type (Borrelli et al., 2017; Yang et al., 2003). By calculating RUSLE twice—first using existing land cover, then changing all land cover to bare soil—the contribution of vegetation to soil retention (i.e., avoided soil erosion) can be estimated as an ES. The RUSLE equation used by this sediment regulation model has several well-known limitations; most notably, it applies only to rill erosion, and does not estimate gully, streambank, or mass erosion. RUSLE was originally developed for agricultural lands in the U.S., though it has since been applied in a wide variety of settings, including ES assessment (Sharp et al., 2015) and global applications (Borrelli et al., 2017; Yang et al., 2003).

2.6. Spatial prioritization and trade-offs between ecosystem services

Assessments of landscape management alternatives often involve the modeling of multiple ES to quantify ES trade-offs, hotspots, and support spatial prioritization according to different stakeholders' perspectives, which could include specific ES beneficiary groups (Nelson et al., 2009). To meet these challenges, ARIES includes an easy-to-use spatial multi-criteria analysis (SMCA) module. Based on the approach developed by Villa et al. (2002), which builds on the Evaluation of Mixed Data (EVAMIX) approach developed by Voogd (1983), the SMCA can integrate quantitative and semi-quantitative measures into a single score.

SMCA uses concordance/discordance analysis, where a set of observations with measured variables (in this case, the potential supply of five ES) is ordered according to a concordance or discordance score computed for each different 'evaluation unit,' described by values for each variable considered. First, a 0 to 1 score is computed using sets of weights that express the importance of each variable from a particular stakeholder's perspective. Each perspective is defined by a 'priority vector' containing the weights assigned to each variable, e.g., by a specific stakeholder type. The scores for all units constitute an 'evaluation matrix.' This is too computationally intensive to calculate on a grid cell basis, but is aggregated by variable values and discretized into a number of intervals (by default the system uses 10 intervals). As the final output, a map of concordance values ranging from 0 to 1 is produced for each stakeholder, distributing the computed scores to each cell. This map represents how concordant the configuration of the landscape is with an optimal landscape, based on a given stakeholder's perspective.

Inputs to the SMCA model include the list of variables to be considered (i.e., ES supply) and a set of importance weights characterizing each criterion. Different stakeholder or ES beneficiary groups can have diverse perspectives on the importance weights. Here, we demonstrate the use of weights by four hypothetical stakeholder groups in the Basque Country: citizens, farmers, local government, and climate activists (Table 1). For simplicity, we used weight values from 1 to 10, with lower values having the greatest weight, but any scale can be used. In the hypothetical example described here, citizens assign the highest importance to recreation and flood regulation; farmers assign the highest importance to pollination, followed by sediment regulation, and to a lesser extent flood regulation; local government officials prioritize all ES as equally important; and climate activists assign the highest importance to carbon storage, and secondary importance to flood and sediment regulation.

Table 1

Priority weights (descending from 1 to 10) assigned to four hypothetical stakeholder groups to each potential ecosystem service (ES) supply, used in the Spatial Multi-Criteria Analysis.

Criteria/ES supply	Citizens	Farmers	Local government	Climate activists
Pollination	10	1	5	10
Carbon Storage	10	10	5	1
Outdoor Recreation	1	10	5	10
Flood regulation	1	5	5	5
Sediment regulation	10	2	5	5

3. Results

We computed mean values and the standard deviation of all ES indicators for all application contexts and models (Supplemental Information, Table S4). We interpret outputs for each ES model from one selected application below. Additionally, we include locator maps for geographic features mentioned in each application in the Supplemental Information.

For pollination, supply and demand in Rwanda and Burundi are generally somewhat mismatched (Fig. 3). As land cover in both nations is increasingly split between natural ecosystems (capable of providing pollinator habitat and found within protected areas, Fig. 3A) and cropland outside of protected areas with demand for pollination (Fig. 3B), these nations may face increasing spatial segregation between areas of pollinator supply and agricultural demand (Fig. 3C–D). However, high topographic and land cover heterogeneity and an abundance of small farms may enable the persistence of some pollinator habitat at finer scales than our model could detect.

The Santa Fe Fireshed region includes a significant amount of land in public ownership, with the vast majority held within the U.S. Forest Service (USFS) system. The highest carbon storage values within this study region fall within USFS lands, particularly in the Sangre de Cristo Mountains to the east of Santa Fe (in the Pecos Ranger District of the Santa Fe National Forest) and in the Cibola National Forest east of Albuquerque

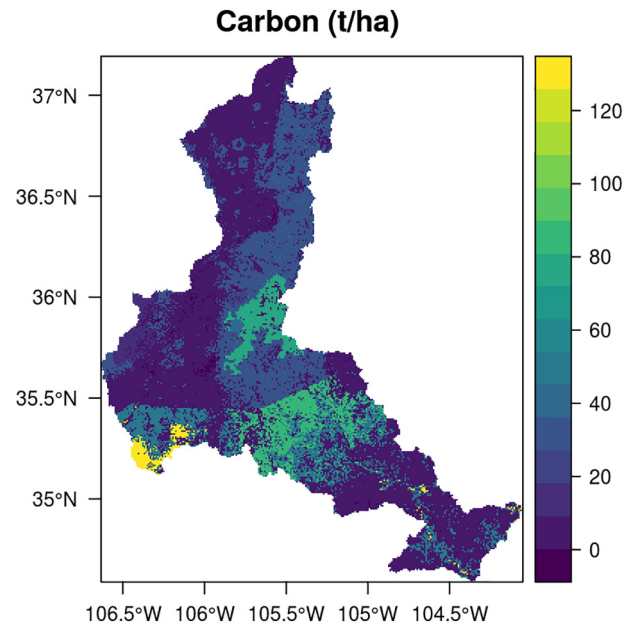


Fig. 4. Results of the carbon storage model in the Santa Fe Fireshed.

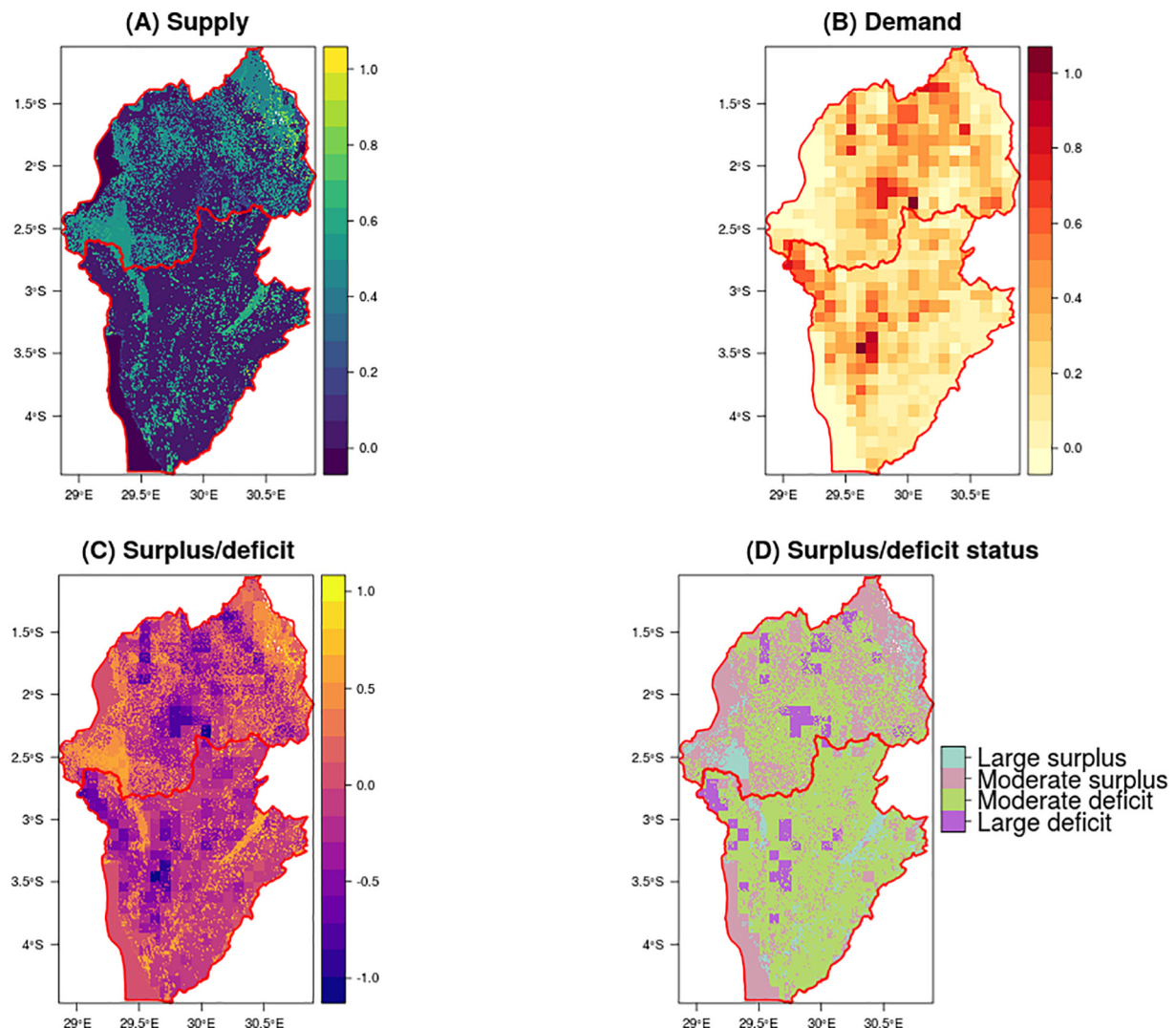


Fig. 3. Main outputs of the pollination model in Rwanda (upper red polygon) and Burundi (lower red polygon): (A) supply, (B) demand, (C) surplus/deficit and (D) surplus/deficit status.

(Fig. 4). Carbon storage in these areas is not evenly distributed, however, due to the presence of both historically burned areas and ongoing fire management, including forest thinning and controlled burns. Carbon storage on land other than publicly managed forests is lower due to the land cover characteristics in these areas (e.g., urban areas, barren lands, grasslands).

The Basque Country landscape is generally rich in potential outdoor recreation opportunities due to the high density of seashores and beaches, freshwater bodies, mountains, and a well-established network of protected areas (Fig. 5A). Recreation demand is centered around three main cities, with the greatest demand in the northwest around the Greater Bilbao metropolitan area (Fig. 5B). Many valuable areas emerge when considering both supply and demand (Fig. 5C), but the greatest value was generated by: (1) beaches and their surroundings near Bilbao and San Sebastián; (2) the coastal and riverine region between these cities, including a Biosphere Reserve (Urdaibai), and (3) the Urkiola mountain range and related protected area, featuring one of the most iconic mountain peaks of the region (Amboto, 1331 m). Other areas have high potential value, but less accessibility. For example, the area surrounding the highest mountain peak (Gorbeia, 1481 m) ranks high in potential value but it is outweighed by other destinations once accessibility and demand are taken into account (Fig. 5D).

Flood regulation surplus in the Basque Country is greatest in watersheds where there is lower population density and abundant natural vegetation that retains runoff (Fig. 6). The largest flood regulation deficits are found in the most populated, impervious, and rainy watersheds of the North, around Bilbao and San Sebastián, where the main rivers discharge and higher flow accumulation occurs.

Avoided soil erosion is generally greatest where existing vegetation protects soils in places that would otherwise be erosion prone, i.e., steep

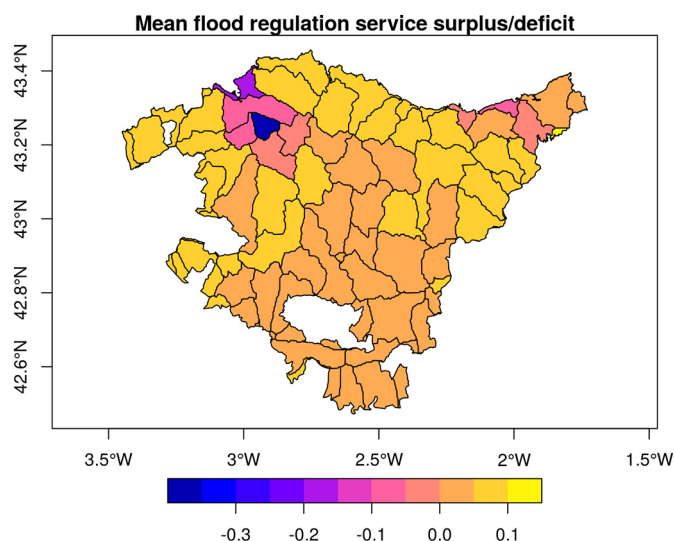


Fig. 6. Mean flood regulation service surplus/deficit (ES_{sd}) by watershed in the Basque Country, ranging from -1 to $+1$. Negative values indicate a flood regulation service deficit, whereas positive values indicate a surplus.

slopes with erodible soils and intense rainfall. Greater soil erosion control is thus found in western Rwanda, where more mountainous to hilly topography and greater annual precipitation occur, and in the Mitumba Mountains of western Burundi—particularly in protected areas in both nations that harbor dense natural vegetation. Less soil erosion control is found in sparsely vegetated areas (i.e., annual croplands) and locations with inherently lower erosion risk, i.e., flatter areas of eastern

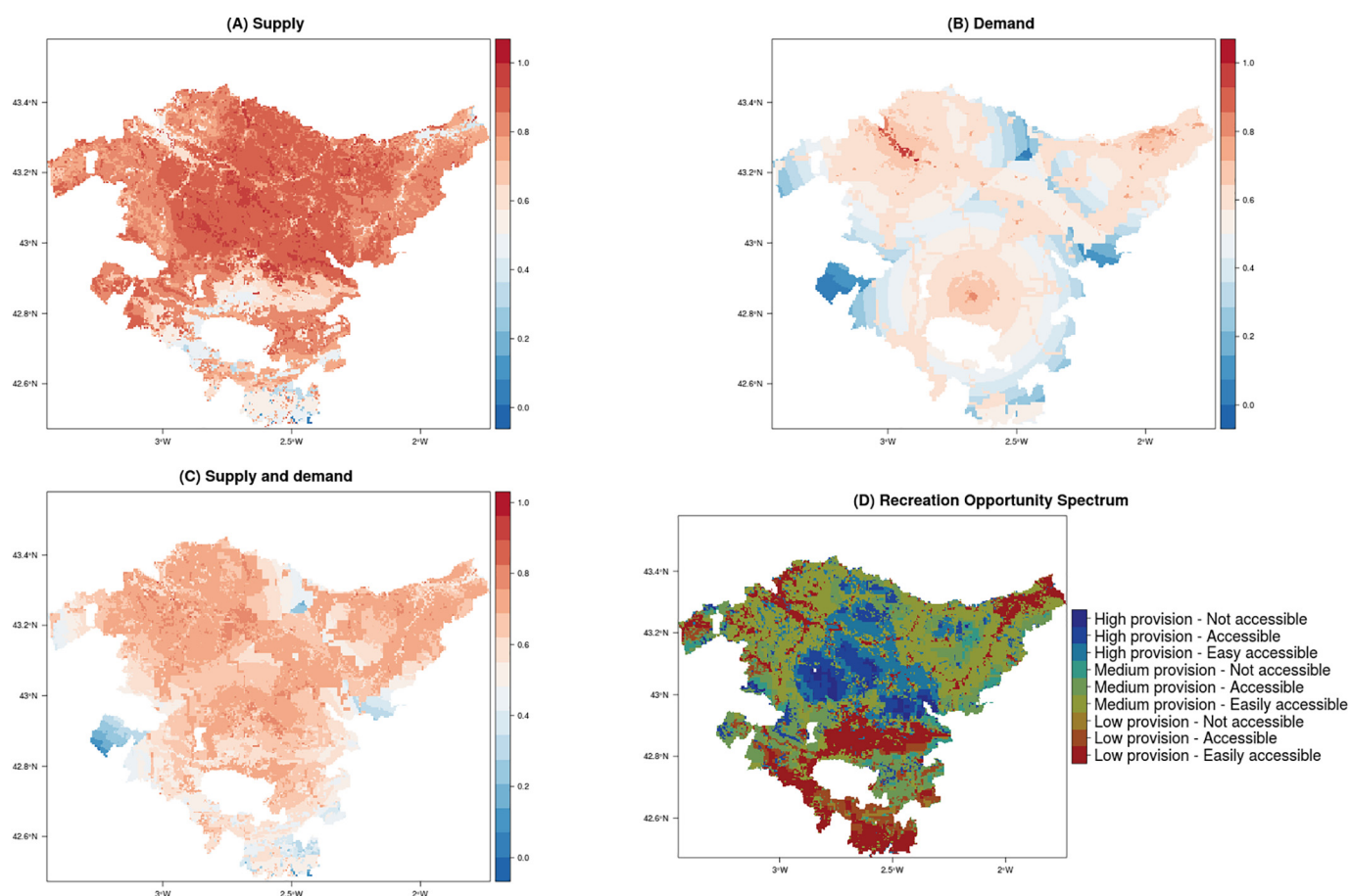


Fig. 5. Main outputs of the recreation model in the Basque Country: (A) supply, (B) demand, (C) supply and demand and (D) recreation opportunity spectrum (ROS).

Rwanda and northeast Burundi, and along the shores of Lake Tanganyika (Fig. 7).

SMCA concordance maps for the Basque Country incorporate ES supply results for all five ES models (Fig. 8). Under the assumption of equal weighting that represents the local government interest (Fig. 8A), high-value areas are scattered throughout the region. Based on the climate activist stakeholder perspective (Fig. 8B), which placed the highest value in areas with the greatest carbon storage, there is an important east-west oriented area in the northern part of the study area, with overlapping higher-value areas for sediment and flood regulation, and one in the mountains located along the region's southern limit. The map of the farmers' perspective (Fig. 8C) is largely explained by the demand for pollination, where high importance occurs in agricultural areas generally, and areas of sunflower seed production (within the plains of Alava) specifically. However, the influence of sediment regulation, also important for farmers (Fig. 8C), is also visible in areas where natural vegetation contributes to soil retention, particularly in the northeast portion of the region (e.g., south of San Sebastián, including the Aiako Harria Natural Park). The Basque Country features significant potential for outdoor recreation (prioritized by citizens, Fig. 8D); most of the region is classified as of potential interest due to the presence of coastline and other water bodies, mountains, and protected areas. High-value areas emerge along a north to south gradient from the coastal Biosphere Reserve (Urdaibai) down to the northernmost part to the plains of Alava, including two large reservoirs and two natural parks (Urkiola and Gorbeia). These parks also offer high levels of flood regulation, making them yet more important to the citizen stakeholder group (Fig. 8D).

4. Discussion

By applying simple but easily customized ES models to three application contexts with diverse ecological and socioeconomic characteristics and data availability, we illustrate ES supply and demand patterns that correspond to expectations based on previous research (Bagstad

et al., 2018b; CDSEA, 2016). However, the results shown above are generated using a specific set of input data, and in an age of rapidly growing data, the standard for “best available data” changes quickly. ARIES provides a platform for quick customization and updating of models as new data become available and are shared on the cloud by a network of modelers. Rather than focusing on specific results, our three applications are thus intended to show the flexibility of this approach in advancing more rapid ES modeling.

Unlike other modeling platforms, k.LAB can directly link diverse modeling techniques (e.g., system dynamics, agent-based models, Bayesian networks, machine learning, GIS algorithms, analytical models, lookup tables, and multi-criteria analyses) and types of knowledge, including quantitative and semi-quantitative data sources and expert opinion (applications of other modeling techniques within ARIES are described elsewhere; Bagstad et al., 2014; Balbi et al., 2015; Willcock et al., 2018). As illustrated in this paper, ARIES models can adapt to the user-selected spatio-temporal context to produce context-dependent results by using the most appropriate data, models, and model parameterizations. Data and model reusability is a fundamental characteristic of ARIES, where semantics support automated workflows linking multi-domain models without requiring added knowledge from the user (Villa et al., 2014). In all cases, data and model provenance is maintained to provide full transparency regarding the choices made during the modeling workflow (Willcock et al., 2018). ARIES also promotes a community-based, knowledge-driven model development strategy, in which data and models are networked, used, and further developed by users, without compromising data confidentiality when restrictions are needed. With the availability of the Tier 1 models described here, ARIES offers sophisticated modeling capabilities to practitioners and decision makers, without imposing a steep learning curve on users, particularly after the forthcoming launch of the web-based ARIES explorer interface.

Automating the matching of available data to model requirements is relatively straightforward for data representing continuous numeric values (i.e., including units of measurement). However, mediation of categorical data, such as land cover, a key input to many ES models (Eigenbrod et al., 2010), poses much more difficult representational challenges for a semantic system. Land-cover mediation for the models described here uses a simple hierarchical term-matching approach. Yet the mediation of user-provided land cover datasets can be challenging, and approaches are needed to appropriately mediate between disparate land cover categories (Ahlqvist et al., 2015; Hansen et al., 2013). The extension of the current linear reasoning approach in k.LAB to the fuzzy reasoning required to handle such problems is a topic for future research.

Currently, the models described here largely use population density to assess ES demand, applying typical indicator-based approaches found elsewhere in the ES literature that can raise awareness of spatial variation in demand, quantify access to ES and their flows, and explore changes in ES supply and demand over time (Wolff et al., 2015, 2017; Paracchini et al., 2014). In evaluating preferences for ES, SMCA can provide a broader view of stakeholder values than monetary valuation alone. SMCA can thus act as a standalone approach to preference elicitation or can complement monetary valuation approaches to ES quantification (Spash and Vatn, 2006). Moving beyond population density-based measures, beneficiary models for individual ES can and should be further developed and customized to local conditions, using more complex indicators and monetary valuation (Wolff et al., 2015, 2017). A modeler could, for example, use per capita gross domestic product (GDP) data to map vulnerable populations and address equity issues, or to infer the economic value of infrastructure at risk (Arkema et al., 2013; Lartera et al., 2016). OpenStreetMap data can also be directly accessed from k.LAB and included in ES demand models (Willcock et al., 2018). We also demonstrated simple aggregation of results by watersheds for hydrologic ES flows (Fig. 6). Similar aggregations could be performed across other geographic units, in order to summarize data

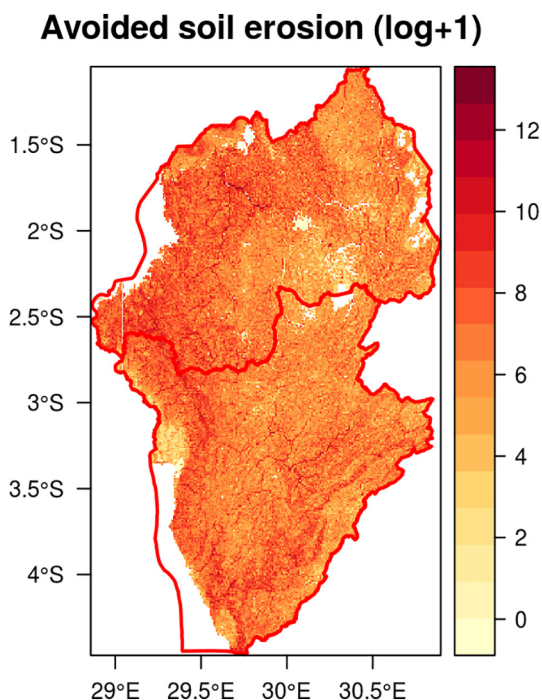


Fig. 7. Avoided soil erosion in Rwanda (upper red polygon) and Burundi (lower red polygon) in t/ha/year. Values are in T/ha, transformed using $\log(x + 1)$.

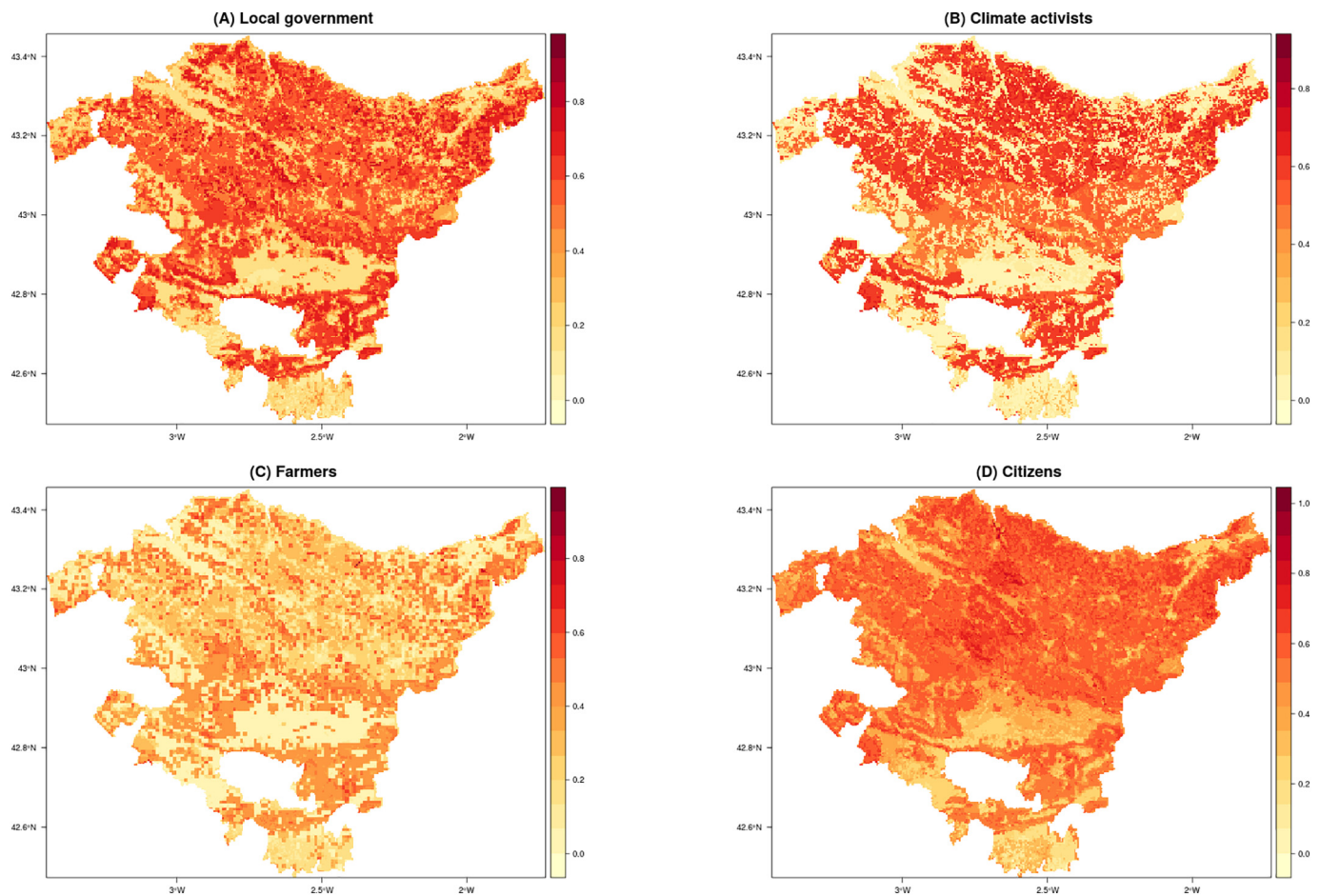


Fig. 8. Spatial multi-criteria analysis (SMCA) concordance maps (from 0 to 1 showing increasing concordance) based on the supply of five potential ecosystem services, applied to the Basque Country for four hypothetical stakeholders' groups: (A) local government, (B) climate activists, (C) farmers, and (D) citizens.

or serve as simple proxies for ES flows that are not computationally expensive.

Data and model customization is important to improve accuracy, transparency, and trust in results used for local applications (Zulian et al., 2018). Without proper documentation and semantic contextualization of participatory processes that generate local knowledge, however, such efforts typically only bear fruit for the initial study, limiting the ability of others to reuse valuable information in future studies (Gray et al., 2017). In addition to data and model customization, ARIES allows users to quantify change through scenarios, substituting alternative spatial, temporal and tabular inputs or conditions for model parameters and variables. For example, modelers can include climate change scenarios in their simulations when running models dependent on climatic variables, such as temperature or precipitation; currently, this can be accomplished in ARIES for a variety of IPCC scenarios (Hijmans et al., 2005).

Data sources that allow redistribution are accessible to all users on the ARIES network. The use of the k.LAB software requires a user certificate, which is free to non-commercial users. Data sources with redistribution restrictions are, naturally, restricted for public use. For instance, models that rely on WorldClim data (e.g., flood regulation and pollination models), rainfall erosivity data (sediment regulation model), and global cropland data (pollination model) which do not allow redistribution, will allow models to be computed as derived products, but visualization or export of input data will not be allowed. The ARIES models refer to data through uniform identifiers (URNs) that are resolved by network servers after user authentication, allowing fine-grained data access permission and giving owners full control of the allowed use of their data or models, either by end users or by other models. Datasets

with no restrictions on redistribution can be fully viewed and exported. Whenever possible, the use of open data and models is most advantageous; open data provide transparency and trust in modeling, while reliance on restricted data makes it more difficult to understand model outputs and troubleshoot any issues that may arise, as access to source information is limited. Although not yet widely discussed in the ES research community, our work on data and model linking and reuse meshes well with initiatives to improve scientific workflows and reproducibility, e.g., through the Findable, Accessible, Interoperable, and Reusable (FAIR) principles (Stall et al., 2017; Wilkinson et al., 2016).

5. Conclusions

Sustainability science needs to account for the dynamic relationships and feedbacks between ES, human well-being, and economic activities (Willcock et al., 2016). The ES models developed in this study, although simple, can be applied in any study area globally without added input, yet can be easily modified to customize models or evaluate the effects of different landscape management alternatives across multiple scales. Additionally, as new datasets for model inputs with greater accuracy, spatial resolution, and temporal density are released, ES models can be quickly updated by users by annotating new datasets and rerunning the models (Bagstad et al., 2018b; de Araujo Barbosa et al., 2015; Martínez-López et al., 2016; Pettorelli et al., 2017; Buchanan et al., 2018). Given the increasing amount and quality of available spatial data, ARIES thus offers a way to keep ES model results as timely as possible. At the same time, ARIES' data and model sharing architecture provides a mechanism for data synthesis and reuse that with wider use

provides greater benefits to the broader ES research and policy communities.

The open data and semantic modeling paradigm—storing data and models on the cloud and sharing them with the scientific community to encourage their linking and reuse—will be most effective as new users join, contribute, and share their own data and models. To this end, the models described here provide a starting point for ES assessments, improving the usability of ARIES models by new users. Short, accessible training courses and documentation, along with user-friendly interfaces, can help introduce more modelers to the ARIES approach, contributing to enlarging the user community.

The customizable Tier 1 models presented in this paper are just a starting point for more sophisticated, flexible, community-driven modeling. Future research directions include the completion of additional Tier 1 ES models, seamless incorporation of agent-based models, and assessment of ES flows, process models, and other Tier 2 models capable of more sophisticated, dynamic analyses where data exist at appropriate spatio-temporal scales. In many cases, Tier 2 models will replace indicator-driven approaches with physically based ones that are amenable to model calibration and can produce more useful predictions through scenario analysis. For example, a Tier 2 version of the pollination model under development is computed continuously over time to quantify monthly and seasonal changes in pollination. This approach would be suitable for localized analysis and is better able to predict both seasonal and interannual effects of climate change on pollination. At the same time, the Tier 1 pollination model will remain usable to provide rapid ES assessment across large spatial extents and/or in data-poor regions.

As we demonstrate in this paper, cloud-based and context-aware ES models offer a way for users to perform quick assessments using an existing base of global data and models (e.g., Burundi) or to customize model structure, inputs, and parameters where data are available (to an increasing degree for Rwanda and the Basque Country and Santa Fe Firehired applications). By more efficiently collaborating and reusing ES knowledge, this approach offers a path towards making ES assessments more accessible, transparent, and rapid, overcoming key roadblocks that have limited the widespread use of ES information in decision making to date.

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Appendix A. Supplemental Information

Supplemental Information to this article can be found online at <https://doi.org/10.1016/j.scitotenv.2018.09.371>.

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